Artificial Intelligence in Consumer Decision-Making: Its Influence on Brand Switching Intentions

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Abstract

The increasing adoption of artificial intelligence in consumer interfaces is changing the way people consider alternatives and brand decisions. Based on the Stimulus-Organism-Response (S-O-R) Model and the Technology Acceptance Model (TAM), this study will investigate how AI-based decision-making affects consumer intentions to switch brand, with special focus on the mediating effects of perceived usefulness and trust. Quantitative research design was adopted wherein data was obtained from 217 participants. Data was collected using structured questionnaires. The findings shows that the existing AI-based decision systems have a substantial impact on the consumer brand switching intention, via the perception of usefulness and trust.

Keywords: Artificial Intelligence, Stimulus-organism-response (S-O-R), Technology Acceptance Model (TAM), Consumer Brand Switching Intention

1. Introduction

Artificial intelligence has changed the way consumers make decisions while purchasing online. The tools like chatbots, AI driven recommendation engines are integrated to platforms used by everyone everyday- which shapes how consumers search products, compare alternatives and ultimately decide what to buy. Beyond only making things more convenient for online buyers it also influences how consumers feel about the brands and whether they stick to the brand or switch (Huang & Rust, 2021; Davenport et al., 2020).

Shopping through online platforms today means coming across plethora of choices, which can be overwhelming. AI here steps in to cut the noise and offers personalised suggestions and streamlining the whole process. But surprisingly it is seen that the more consumers come across and lean on AI generates recommendations, the more the loyalty towards brand shifts. What once felt like a firm choice can become flexible when algorithms are involved and keeps changing consumer attention in a different direction (Shankar, 2018). This raises an important question on understanding what actually going on in a person's mind while coming across these types of AI recommendations?

To make a understanding of the same the study has adopted two frameworks: the Stimulus- Organism-Response (S-O-R) model and the Technology Acceptance Model (TAM). The S-O-R helps us to understand that something in the environment named stimulus triggers mental and emotional responses internally in the organism, which drive the behaviour of the organism as a response (Mehrabian & Russell, 1974). So, in this case the AI system is acting as a stimulus, the internal response is how helpful, useful and trustworthy the consumers find it, and the behaviour whether consumers stay or switch to other brands. Similarly, TAM here adds another layer by pointing out that people (here consumers) are more likely to accept and embrace a technology which they genuinely believe will help them. (Davis, 1989).

Perceived usefulness means whether AI tool actually helping a consumer makes decision better. Research indicates when people find AI helpful, they tend to rely on it more and that reliance can quietly reshape their brand preferences over time (Venkatesh et al., 2003). As AI always is not transparent in its way of operation, consumers need to feel confident that the recommendations they're getting are reliable and credible (Glikson & Woolley, 2020). The more the trust the system, the more they rely on the system and the more they become open to switch to brands.

That being said, there is still a noticeable gap in the existing literature. Most studies on AI in marketing have focused mainly on things like how people adopt to new technologies, how personalization works, or what kind of experience personalization creates but limited studies are found to connect AI and brand switching as an outcome. While the role of AI in consumer decision making is widely studied, the exact mechanism that led to brand switching haven't been explored nearly enough.

In some previous studies (Glikson & Woolley, 2020; Gefen et al., 2003) we get some hints of factors like perceived usefulness or trust and their impact on consumer decision making but we rarely found study considering both of them together. For this study the S-O-R framework offers a strong foundational model and we also found out that it hasn't be used in the context of AI driven decision system and brand switching in many related studies.

Given the same, there's a clear need to dig deeper into how AI shapes brand switching behaviour and more specifically what role perceived usefulness and trust play in that process. This study aims to answer three questions: 1) How do AI- driven decision systems affect perceived usefulness and trust? 2) Do perceived usefulness and trust push consumers toward switching brands? 3) Do perceived usefulness and trust mediates the relationship between AI driven systems and brand switching decision?

To answer the same, the study builds and tests a comprehensive framework that brings together AI- driven decision systems, perceived usefulness, trust and brand switching intentions using a quantitative approach. Furthermore, AI-driven decision-making by consumers is context-specific and especially so when it comes to categories. Existing studies indicate that the impacts of digital technologies differ between high- and low-involvement categories, and by consumers' familiarity and experience. For example, in categories like electronics and apparel, where consumers often encounter AI-based recommendations, the propensity to consider alternatives and brand switching is relatively high. Thus, the study of AI-driven decision-making without considering the specific contextual setting may limit the insights about consumer reactions.

To overcome this limitation, the current research examines consumers perception in online apparels category, as well as consumer characteristics for the same category, including purchase frequency and experience. This helps capture the impact of AI-driven decision systems on consumers brand switching intentions in naturalistic consumption contexts.

2. Theoretical Background

The Stimulus-Organism-Response Model offers a holistic perspective on consumers' behaviour in technology-enabled settings. In this model, AI-driven decision systems serve as external stimuli that evoke consumers' cognitive and emotional responses. In particular, perceived usefulness is the cognitive assessment of the performance of AI recommendations, and trust is the social trust in AI. These perceptions, in turn, affect behaviours, such as intentions to switch brands.

Similarly, the Technology Acceptance Model describes how consumers perceive and use technological systems in terms of usefulness. But in AI settings, trust is also vital as algorithms are not fully transparent and operate autonomously. The current study brings together S-O-R and TAM to offer a comprehensive model that explains cognitive and relational aspects involved in AI-driven behaviours.

2.1 Stimulus–Organism–Response (S-O-R) Framework

An initial paradigm of defining the impact of external environmental factors on individual behaviour can be found in the Stimulus-Organism-Response Model, which was originally introduced by Mehrabian and Russell (1974). It is a model that environmental stimuli (S) influence internal cognitive and emotional states (O) which in turn cause behavioural responses (R). The S-O-R framework has been extensively used in explaining the influence of technological and environmental cues on consumer perceptions and behaviour in the context of digital consumer behaviour (Eroglu et al., 2001; Jacoby, 2002). In this research, AI-based decision systems can be viewed as the stimulus as they are external technology inputs that can affect the decision-making process of consumers. Internal psychological states, namely, perceived usefulness and trust, represent the organism and depict cognitive appraisal and relationship trust in AI systems. The behavioural outcome is the consumer brand switching intentions which capture the response. This study offers a systematic way of interpreting the impact of AI-driven systems on consumer behaviour by the means of psychological mechanisms by using the S-O-R framework.

2.2 Technology Acceptance Model (TAM)

One of the most popular models that have been used to explain user acceptance of technology is the Technology Acceptance Model by Davis (1989). The model recognizes perceived usefulness and perceived ease of use as the key determinants of technology adoption.

Out of these, perceived usefulness is a key factor in determination of user attitudes and behavioural intentions. It is the degree to which a person feels that one system is more effective in increasing their performance or efficiency in making decisions (Davis, 1989; Venkatesh et al., 2003). Perceived usefulness in AI-driven settings indicates how much consumers think that AI systems can enhance the quality and efficiency of their buying behaviors. Trust has proven to be a decisive criterion in technology-mediated interactions, especially in AI settings with complexity in algorithms and a lack of transparency (Glikson and Woolley, 2020). Trust is a complement of the TAM in that it considers some relational dimensions of the adoption of the technology hence giving a more detailed picture of consumer behaviour.

3. Literature Review and Hypotheses Development

3.1 AI-Driven Decision Systems and Consumer Behaviour

AI-based systems of decision-making have become a revolutionary trend on the modern consumer markets that turn the process of information research, alternative consideration, and purchase choices on its head. Machine learning algorithms and sophisticated analytics underlie these systems and use huge volumes of consumer data, which include browsing history, previous purchases, or contextual signals, to provide highly personalized recommendations (Huang and Rust, 2021; Davenport et al., 2020). In this way, they help minimize information overload and make complex decision-making scenarios easier, facilitating more effective navigation of the increasingly digital marketplace by consumers.

There is a behavioural perspective, where AI-based systems change the conventional decision-making approaches by transforming the consumers into consumers who resort to algorithm-assisted decision making outside of self-assessment. Consumers no longer actively find and compare various choices, but rather turn to the suggestions offered by AI systems (Shankar, 2018). This revolution can be seen especially with online retail systems like that of apparels, where recommendation systems steer product exploration and impact selection sets. As a result, the AI systems do not only facilitate the decisions but also influence the consumer preferences and perceived alternatives (Libai et al., 2020).

Furthermore, the AI-based decision systems are also instrumental in shaping perception and attitudes of consumers. Individualized suggestions are capable of increasing perceived relevancy and satisfaction, which can lead to an improved consumer experience overall. Consumers are likely to use AI systems when they view the latter as able to comprehend their likes and dislikes, when they become more interested in the platform and want to consider the proposed alternatives. Such enhanced interest can usually be translated into exploratory behaviour, in which consumers are more readily disposed to adopt new and unknown brands or products, and this subsequently influences brand choice and change behaviour.

Nevertheless, AI does not affect the consumer behaviour in a completely positive way. Research in the new literature reveals issues to do with the aversion to algorithms, where consumers become opposed to AI suggestions because of the lack of transparency or any perceived loss of control (Castelo et al., 2019). The uncertainty that may emerge as a result of the black box-type nature of AI systems can make consumers doubt the credibility and fairness of recommendations (Puntoni et al., 2021). Also, the perception of users can be complicated by other factors, like data privacy and bias in algorithms; it may decrease trust and inhibit the usefulness of AI-based interventions.

The other significant dimension is whether contextual and individual factors contribute to moderating the effects of AI-led systems. The efficacy of AI recommendations can also differ by the type of products, consumer engagement, and the extent of the purchasing experience. An example of this is that in categories with low involvement or high frequency of purchase, consumers can easily take AI recommendations because perceived risk is less. However, in high-involvement categories, including electronics or financial services, consumers might have a more deliberative process and algorithmic recommendations are less important. In the same manner, new consumers might rely more on AI to guide them; however, when the consumers are more experienced, they might develop a higher level of doubt and independence in their decision-making.

Although such complexities exist, AI decision systems remain at the core of contemporary consumer behaviour. These systems are powerful stimuli in digital spaces, as they can affect consumer perception of alternatives, evaluation of alternatives and decision-making. The personalisation of experiences and influencing the decision-making processes they can do put them in the position of drivers of behavioural outcomes, such as engagement, satisfaction, and brand switching intentions. With the current development of AI technologies, the analysis of their influence on the consumer behaviour becomes more important both to the researchers and practitioners that aim to manoeuvre in the quickly evolving environment of online marketing.

Brands using AI present personalized recommendations influenced by the information gathered about the user, which can affect the choice of brands due to machine learning tools such as AI driven recommendation software, AI assistants, and algorithm-based platforms (Huang and Rust, 2021; Davenport et al., 2020; Libai et al., 2020). Under these AI driven decision systems, there is less information gaps that results in more efficiency, speediness and accurate decision making. Consequently, preference trends start to change under the impact of AI-based algorithmic designs (Shankar, 2018; Brynjolfsson and McAfee, 2017). In theoretical perspective, Stimulus-Organism-Response Framework can be used to explain this phenomenon.

The internal emotion and feelings influenced by external stimuli such as AI driven decision system led to actions such as brand switching (Mehrabian and Russell, 1974; Eroglu et al., 2001). As AI based decision systems increasingly impact consumer-brand interactions, they carry a high potential to influence switching behaviour by exposing consumers to alternative options (Grewal et al., 2020; Puntoni et al., 2021). The same has been represented in Figure 1.

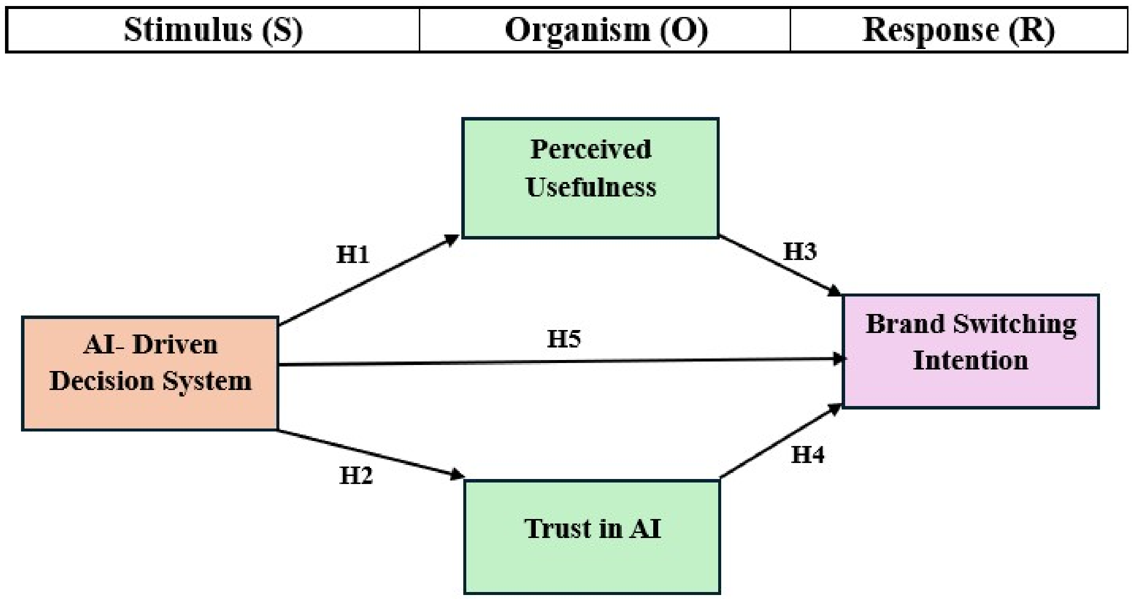

Figure 1- Conceptual Model
Source(s): Author's own creation

2.2 **AI-Driven Decision Systems and Perceived Usefulness**

Perceived usefulness acts as the central core of the Technology Acceptance Model. This framework measures how much someone thinks using a given system helps them do better work (Davis, 1989). When applied to AI-driven decision systems, perceived usefulness reflects the degree to which consumers believe that AI recommendations improve their decision quality and efficiency.

Previous researchers have also proven that AI-based systems contribute to perceived usefulness through delivering personalized, timely, and relevant information (Venkatesh et al., 2003; Gefen et al., 2003; Wang and Benbasat, 2007). Once consumers think that AI systems are helpful, they will tend to use them in the decision-making process, thus, they will tend to evaluate their brands differently and be more likely to switch (Tam & Ho, 2006; Xiao and Benbasat, 2007). Furthermore, the capacity of AI systems to handle data in large quantities and provide specific recommendations is another factor that contributes to their perceived usefulness (Huang and Rust, 2021; Shankar, 2018).

Hypothesis Development

H1: There is a significant positive effect of AI-driven decision systems on perceived usefulness.

2.3 Decision systems and Trust based on AI

One of the key elements of consumer acceptance and dependency on AI technologies is trust. It has an impression that a system is trustworthy, reputable and has the capacity to provide true and objective advice (Gefen et al., 2003; McKnight et al., 2011). Under AI-driven conditions, trust is especially crucial because the process of making decisions based on algorithms is autonomous and frequently opaque (Glikson and Woolley, 2020; Castelo et al., 2019). Studies indicate that consumers tend to embrace and use AI systems more when they believe that they are trustworthy (Chattaraman et al., 2019; Araujo et al., 2020). Trust lessens the uncertainty and perceived risk thus increases the impact of AI suggestions on consumer decision-making (Pavlou, 2003; Gefen et al., 2003). Therefore, the more trust in AI systems, the more openness of consumers towards alternative brand suggestions, which are more likely to induce switch behaviour (Puntoni et al., 2021).

Hypothesis Development

H2: AI-based decision systems positively influence the level of trust.

2.4 Perceived Usefulness and Brand Switching Intentions

Perceived usefulness is an important factor that influences consumer behavioural intentions. TAM argues that people tend to use and depend on technologies that they consider to be helpful (Davis, 1989; Venkatesh et al., 2003). Within the framework of consumer decision-making, AI-driven systems are perceived as useful; therefore, consumers can depend on their recommendations more, although it can require changing the previously preferred brands.

Empirical research shows that improving the decision support and efficiency may prompt consumers to re-evaluate their current brand preferences and consider other options (Tam & Ho, 2006; Shankar, 2018). Since the recommendations offered by AI are optimized and customized, they can prompt consumers to change brands and switch to those that better represent their preferences (Huang and Rust, 2021).

Hypothesis Development

H3: Perceived usefulness has a significant positive influence on consumer brand switching intentions.

2.5 Trust and Brand Switching Intentions

Consumer behaviour in the digital world is largely affected by trust. As consumers will have trust in AI-based decision systems, they will be more willing to base their decisions on their suggestions and think about other options that these systems propose (Gefen et al., 2003; Pavlou, 2003). Trust lessens the perceived uncertainty and boosts confidence in making the decisions, hence the higher the chances of behavioural change. Trust in the recommendations of AI in AI-mediated situations may prompt consumers to abandon their habitual brand decisions and seek alternatives (Glikson and Woolley, 2020; Araujo et al., 2020). This implies that trust does not merely enable technology adoption but is also influential in influencing brand switching behaviour.

Hypothesis Development

H4: Trust positively affects consumer brand switching intentions.

2.6 Direct impact of AI-Driven Decision System on Brand Switching

In addition to indirect effects, the consumer brand switching behaviour can be directly affected by AI-driven decision systems. These systems can break the brand loyalty and prompt switching by constantly exposing consumers to individualized options and competitive products (Grewal et al., 2020; Libai et al., 2020).

According to the S-O-R model, the effects of stimuli may be both direct effects on behaviour and indirect effects via organismic states (Mehrabian and Russell, 1974). In that regard, AI-driven decision systems can have a direct influence on brand switching intentions by influencing consumer attention and processes of evaluation (Puntoni et al., 2021).

Hypothesis Development

H5: AI-driven decision systems have a significant positive impact on consumer brand switching intentions.

2.7 Mediating role of Perceived Usefulness and Trust

Expanding on the Stimulus-Organism-Response Model, perceived usefulness and trust are organismic variables mediating the association between AI-based decision systems and consumer reactions. The empirical studies indicate that both cognitive (usefulness) and relational (trust) variables lead to behavioural effects in technology-mediated ecosystem (Venkatesh et al., 2003; Gefen et al., 2003; Glikson and Woolley, 2020).

The perceived usefulness and trust provided by AI-driven systems positively influence consumer reliance on AI recommendations and consumer behaviour switch. This implies that there is a two-way mediation process by which AI can affect consumer behavior.

Hypothesis Development

H6: Perceived usefulness mediates the association between AI-driven decision systems and consumer brand switching intentions.

H7: There is a mediating effect of trust between AI-driven decision systems and consumer brand switching intentions.

3. Research Methodology

3.1 Questionnaire Development

Data were gathered using a structured questionnaire. To provide reliability and validity, the measurement items of all the constructs were modified based on the previous scales that were validated. In particular, the items that quantified AI-driven decision systems were based on previous research related to AI-enabled decision systems and decision support technologies (Huang and Rust, 2021; Wang and Benbasat, 2007). Perceived usefulness measurement items were modified based on the Technology Acceptance Model (Davis, 1989; Venkatesh et al., 2003). Items for trust were derived based on previous literature on trust in technology (Gefen et al., 2003; McKnight et al., 2011). Also, brand switching intention was assessed on the basis of the items that were adapted to preceding studies on consumer behaviour and switching (Bansal et al., 2005; Keaveney, 1995).

After identifying measurement items, the questionnaire was narrowed down according to earlier research suggestions (e.g., Kumar et al., 2023; Liao et al., 2023), where the items were rephrased to be specific to AI-driven decision systems. Expert evaluation was also carried out to provide face validity as recommended by Hsieh et al. (2012) and Talwar et al. (2024). Three academic experts and one industry practitioner reviewed the questionnaire and their suggestions, including simplification of language, elimination of ambiguity and enhancing clarity, were taken into consideration.

To improve the clarity, consistency, and understandability of the instrument, to eliminate possible semantic problems, a pretest was conducted (Bell et al., 2022). This process aided in developing content validity. A pilot study was then carried out on 34 respondents to evaluate the reliability and validity of the measurement instrument before a full-scale data collection was done. In line with previous studies (Bhardwaj et al., 2023; Hsieh et al., 2012 and Kumar et al., 2016), open-ended feedback was also suggested to the respondents to make further improvements.

Pilot test outcomes showed a positive outcome of measurement items with a factor loading of above the recommended threshold of 0.60 (Hair et al., 2018). Moreover, the alpha of all constructs was more than 0.70 which is quite good internal consistency. These findings validated that the questionnaire could be used in full-scale data collection.

Each of the items was measured on a five-point Likert scale, with a range of 1 (strongly disagree) to 5 (strongly agree).

3.2 Data Collection

The researcher used non-probability convenience sampling approach, which is typical of behavioural studies, in which the respondents are chosen according to their availability and readiness to take part (Etikan et al., 2016). A structured questionnaire was used to gather data using online means.

The valid responses collected were 217 in total, and it was analyzed. This sample size is deemed to be sufficient to conduct multivariate analysis and SEM, which is recommended by methodological guidelines (Hair et al., 2019). Also, earlier research works by Rummel (1970) and Schwab (1980) justify the sufficiency of such samples in analysis of statistical data on social science research.

The sample of respondents was comprised of people who had the previous experience of using digital platforms to purchase apparels and they were classified as frequent users/moderate users/occasional users on the basis of their frequency of purchase (Wedel, M., & Kamakura, W. A., 2000). This made certain that the participants were adequately exposed to the constructs to be studied.

4. Results and Findings

Test of Reliability

Cronbach Alpha (CA) and Composite Reliability (CR) were used to measure the reliability of the constructs. Cronbach Alpha and Composite Reliability values were found to be 0.822- 0.872 and 0.823- 0.873 respectively as indicated in Table 1. The constructs were all above the suggested value of 0.70 which shows high internal consistency and reliability. The fact that the CA and CR values are very close to each other further assures that the measurement model is stable and consistent.

Variables/ Constructs	**Cronbach Alpha (CA)**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
AI – Driven Decision System (AIDeS)	.853	.854	.540
Perceived Usefulness (PU)	.872	.873	.580
Trust in AI (Trust)	.822	.863	.559
Brand Switching Intention (BSI)	.863	.823	.553

Table 1- Reliability and Convergent validity
Source(s)- Author's own creation

Average Variance Extracted (AVE) was used to measure convergent validity. Observations (in Table 1) have shown that all constructs obtained AVE values above the recommended value of 0.50 (Fornell and Larcker, 1981) with AIDeS (0.540), perceived usefulness (0.580), trust (0.559) and brand switching intention (0.553). These values indicate that both constructs account for over 50 per cent of the variance of their indicators, thus supporting sufficient convergent validity of the measurement model.

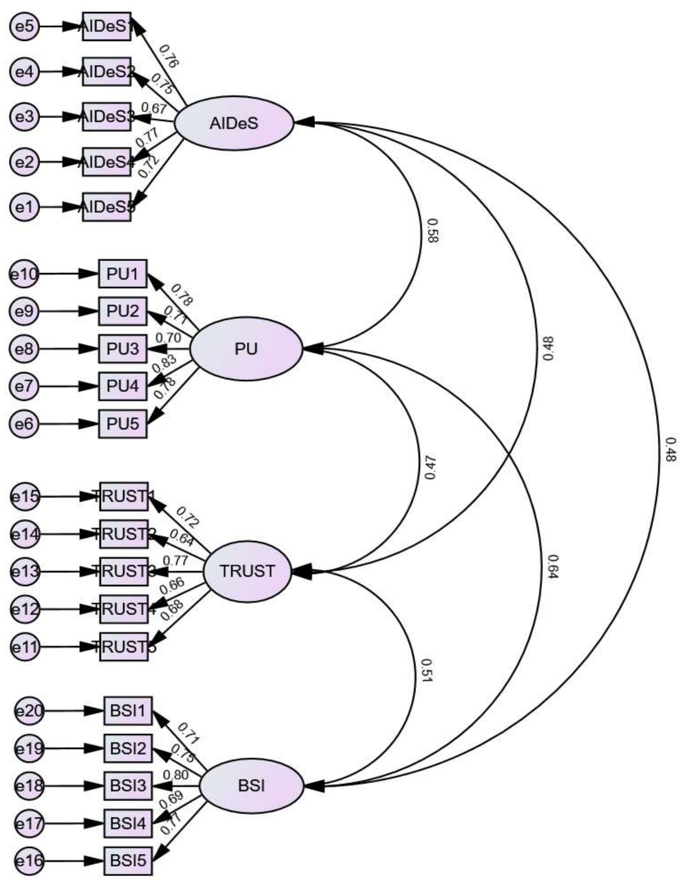

Figure 2- Reliability Test

Source(s): Analysis using AMOS

Variables/ Constructs	Items	Source	Standardized Factor Loadings
AI – Driven Decision System (AIDeS)	AI-driven systems provide recommendations that match my preferences.	Wang & Benbasat (2007)	.760
	I find AI-based recommendations to be accurate.	Xiao & Benbasat (2007)	.750
	AI systems help me discover new apparel products or brands.	Huang & Rust (2021)	.674
	AI-driven platforms provide personalized suggestions relevant to me.	Wang & Benbasat (2007)	.768
	I rely on AI-generated recommendations while making purchase decisions.	Xiao & Benbasat (2007)	.717
Perceived Usefulness (PU)	AI-driven systems improve my decision-making effectiveness.	Davis (1989)	.777
	AI recommendations make it easier to choose between brands.	Venkatesh et al. (2003)	.711
	Using AI systems enhances my shopping efficiency.	Davis (1989)	.704
	AI-driven suggestions are useful in evaluating alternatives.	Venkatesh et al. (2003)	.828
	AI systems are beneficial for making purchase decisions.	Davis (1989)	.780
Trust in AI (Trust)	I trust the recommendations provided by AI systems.	Gefen et al. (2003)	.721
	AI-driven systems provide reliable information.	McKnight et al. (2011)	.643
	I feel confident relying on AI suggestions.	Gefen et al. (2003)	.771
	AI systems act in my best interest while recommending products.	McKnight et al. (2011)	.656
	I believe AI recommendations are credible.	Glikson & Woolley (2020)	.676
Brand Switching Intention (BSI)	I am likely to switch brands based on AI recommendations.	Bansal et al. (2005)	.714
	AI suggestions encourage me to try new brands.	Keaveney (1995)	.754
	I would consider switching from my preferred brand if AI suggests a better option.	Bansal et al. (2005)	.800

	AI-driven recommendations influence my decision to change brands.	Keaveney (1995)	.694
	I am willing to explore alternative brands suggested by AI systems.	Bansal et al. (2005)	.771

Table 2- Items, Construct and Standardized factor loadings
Source(s): Author's own creation

For measuring the reliability of the indicators, the standardized factor loadings of all measurement items were tested. The same is represented in Table 2 and Figure 2. The findings suggest that the loadings were between 0.643 and 0.828, with most of the items having a higher load than the recommended value of 0.70 (Hair et al., 2019). Even though some of the items had slightly lower loadings, they were still at a good enough level of 0.60, which is sufficient to contribute towards their constructs. On the whole, the findings indicate that each of the items exhibits high levels of reliability in indicators and can be incorporated into the measurement model.

Discriminant Validity

	AIDeS	**PU**	**BSI**	**Trust**
AIDeS	**0.735**			
PU	0.578	**0.761**		
BSI	0.484	0.635	**0.748**	
Trust	0.478	0.466	0.513	**0.743**

Table 3- Discriminant Validity
Source(s): Author's own creation

The Fornell Larcker criterion was used to determine discriminant validity (Fornell and Larcker, 1981). The same is represented in Table 3. Based on this method, the square root of the Average Variance Extracted (AVE) of each construct is supposed to exceed inter-construct correlations. The square root of the AVE of all constructs, including AI-Driven Decision Systems (0.735), Perceived Usefulness (0.761), Brand Switching Intentions (0.748), and Trust (0.743) were greater than the inter-construct correlation coefficients as shown in Table X. This shows that the constructs have more variance with itself indicators compared to other constructs, thus establishing sufficient discriminant validity. The findings indicate that the constructs are empirically different and they measure different conceptual areas, which confirms the validity of the measurement model.

Hypothesis Testing

Hypothesis	Relationship	β	t-value	p-value	Supported
H1	**AIDeS → PU**	0.498	8.42	0.000	Yes
H2	**AIDeS → Trust**	0.409	6.57	0.000	Yes
H3	**PU → BSI**	0.546	9.56	0.000	Yes
H4	**Trust → BSI**	0.429	6.96	0.000	Yes
H5	**AIDeS → BSI**	0.411	6.61	0.000	Yes

Table 4- Hypothesis Testing
Source(s): Author's own creation

The hypothesis testing (represented in Table 4) results show that all the proposed relationships are positive and statistically significant. Specifically, AIDeS has a significant effect on perceived usefulness (β = 0.498, t = 8.42, $p < 0.001$) and trust (β = 0.409, t = 6.57, $p < 0.001$), supporting H1 and H2. Moreover, perceived usefulness has a strong impact on brand switching intentions (H3): 0.546, t = 9.56, $p < 0.001$ and trust has a strong impact on brand switching intentions (H4): 0.429, t = 6.96, $p < 0.001$. Moreover, AIDeS also have a considerable direct impact on brand switching intentions (0.411, t = 6.61, $p < 0.001$), which confirms H5. On the whole, each of the hypotheses (H1-H5) is accepted, which means that both cognitive (perceived usefulness) and relational (trust) variables are important and contribute to consumer brand switching behaviour.

Mediating effects

Path	β	P-value	Supported	LLCI	ULCI
Total Effect **AIDeS → BSI**	0.416	0.000	Yes	0.2926	0.5411
Mediating Effect **AIDeS → Trust → BSI**	0.199	0.000	Yes	0.1276	0.2777
Mediating Effect **AIDeS → PU→BSI**	0.165	0.000	Yes	0.1245	0.2176

Table 5- Mediation Effect
Source(s): Author's own creation

The bootstrapped mediation analysis showed that the overall effect of AIDeS on BSI is significant (positive) (0.416, $p < 0.001$; LLCI = 0.2926, ULCI = 0.5411). The indirect effects were significant through both mediators: trust (β = 0.199; LLCI = 0.1276, ULCI = 0.2777) and perceived usefulness (β = 0.165; LLCI = 0.1245, ULCI = 0.2176). The results suggests partial mediation effect of AIDeS on BSI through Trust (mediation percentage= 47.8%) and partial mediation effect of AIDeS on BSI through Perceived Usefulness (mediation percentage= 39.6%) which proves hypothesis H6 and H7.

5. Discussion and Implications

5.1 Discussion of Findings

The study investigated how AI-based decision systems affect consumer intentions to switch brands with perceived usefulness and trust as mediating variables. The results have a high level of empirical support of the proposed framework and have valuable information on AI-enabled consumer behaviour. To begin with, the findings show that AI-based decision systems impact perceived usefulness and trust significantly and positively. This implies that consumers believe that AI systems are useful, efficient, and reliable in helping them to make decisions. These results align with the existing studies that identified AI as an effective means to enhance consumer experience by personalizing and providing recommendations based on data (Huang and Rust, 2021; Shankar, 2018).

Conceptually, this strengthens the relevance of the Technology Acceptance Model, in which perceived usefulness is a major factor that dictates technology usage. Second, the perceived usefulness has been revealed to have a significant role on brand switching intentions. It means that the more consumers see AI-driven systems as helpful, the more they will follow their suggestions, even though it may require leaving the previously popular brands.

This is in line with previous research that positive changes in decision support may transform consumer preferences and diminish inertia in brand selection (Venkatesh et al., 2003; Tam & Ho, 2006). Third, trust in

AI was found to have a significant positive effect on brand switching intentions. Due to the autonomous and algorithmic characteristics of AI systems, trust is a vital aspect of whether consumers believe and respond to AI recommendations. The results align with the existing literature that states that trust minimizes uncertainty and increases the dependency on digital systems (Glikson and Woolley, 2020; Gefen et al., 2003).

Moreover, direct impact of AI-based decision systems on brand switching intentions was also important, meaning that AI systems do not only impact behaviour by cognitive and relational means, they also have a direct persuasive influence on customers. This underscores the increasing strength of AI as a proactive force in influencing consumer decisions. Notably, the mediation test results indicated that perceived usefulness and trust partially mediate the relationship between AI-driven decision systems and brand switching intentions. This observation is a significant support of the Stimulus-Organism-Response Model, in which AI systems (stimulus) have an effect on internal states (organism), which in turn motivate behavioural action (brand switching). The fact that there is partial mediation implies that both direct and indirect processes co-exist in explaining AI-based consumer behaviour.

5.2 Theoretical Implications

This paper contributes to the body of research on digital consumer behaviour and AI in marketing in several ways. To begin with, it generalizes the Stimulus-Organism-Response Model to AI-based decision-making scenarios by empirically confirming the presence of perceived usefulness and trust as organismic factors that affect behavioural consequences. Although previous studies have used S-O-R in the context of online retail, it is not widely used in conjunction with AI-based systems.

Second, the paper combines the Technology Acceptance Model with the theory of trust to achieve a more detailed perspective on consumer behaviour in the AI-mediated setting. The combination of cognitive (usefulness) and relational (trust) constructs enables the research to provide a more holistic explanation of the effects of AI on brand switching.

Third, the research adds to the body of literature on brand switching by centralising AI-powered decision systems in the role of an antecedent of switching behaviour. The past studies have mainly been on price, satisfaction and quality of service, but this study emphasizes the influence of technology as a switching motivator.

Lastly, the research offers empirical data as to the dual mediation effects, thus enhancing methodological rigor in consumer research on AI. This adds to the accumulating literature that notes the need to study indirect effects during technology adoption research.

5.3 Managerial Implications

This study has a number of practical implications to marketers, managers of digital platforms, and companies that use AI technologies. To start with, companies need to invest in improving the perceived usefulness of AI-based systems. This can be achieved through increasing the precision of recommendations, customization and relevance. The marketing strategy is more effective as positive perception of the system increases the likelihood of consumers using AI systems to assist them in making decisions.

Second, it is essential to establish trust in AI systems. In order to develop consumer trust, companies must strive to achieve transparency, reliability, and ethical AI practices. Trust can be improved through the provision of explanations of recommendations (explainable AI) and data privacy.

Third, AI-driven systems can be used strategically by marketers to change brand switching behaviour. The firms will be in a position to win customers of different brands by providing a competitive choice and personal recommendations. This underscores the possibility of AI as an effective customer acquisition tool.

Fourth, businesses should realize that AI technologies not only act as a support system but also influence decision-making. Therefore, AI applications in customer touchpoints (e-commerce platforms, mobile apps, and interactive interfaces) can be used to enhance their engagement and influence the consumer choice.

Last but not least is that the firms ought to constantly measure and streamline AI-mediated communications to keep them in line with the consumer expectations and preferences. This will help in maintaining customer relationship in both the long-run and in taking advantage of switching opportunities.

6. Future Research Directions

Our study provides opportunities for future research.

First, future research can apply the model to other product categories to understand if the effects of AI-based decision systems differ between high- and low-involvement categories. These comparisons can offer greater insights into category-specific consumer decision making.

Second, future studies can use longitudinal designs to examine the dynamics of consumer trust and dependence on AI systems as they gain more experience and familiarity with them. With increased exposure to AI, consumers' attitudes and behaviour may be altered.

Third, future studies should consider other factors such as perceived risk, algorithm transparency, and user control to gain a deeper insight into AI-based decision-making. These variables are important in terms of algorithmic bias and trust issues.

Fourth, cross-cultural research can be undertaken to understand the impact of cultural factors on consumer responses to AI-driven systems, particularly in emerging markets with rapidly growing digital literacy.

Finally, future research can examine moderating factors such as consumer expertise, involvement, technology readiness, to gain insights into the moderating factors of AI-driven consumer behaviour.

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